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## A STUDY OF FUNCTIONAL ITERATIVE APPROACHES FOR TWIN BOUNDED SUPPORT VECTOR MACHINES WITH SQUARED PINBALL LOSS

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## ABSTRACT

Twin Bounded Support Vector Machines (TBSVMs) have emerged as an effective machine learning tool, particularly in handling classification problems. By simultaneously solving two smaller quadratic programming problems, TBSVMs are computationally more efficient compared to traditional Support Vector Machines (SVMs). The incorporation of a squared pinball loss function into TBSVMs introduces further robustness by accommodating asymmetric noise distributions and better handling of misclassified data. This combination enhances model performance, especially in real-world scenarios with imbalanced or noisy datasets. Functional iterative approaches play a pivotal role in optimizing TBSVMs with squared pinball loss. These iterative methods aim to minimize the modified loss function while adhering to constraints that define the twin hyperplanes. The squared pinball loss, as a convex loss function, penalizes deviations based on their magnitude, ensuring more precise adjustments during iterations. Iterative algorithms refine hyperplane placement, effectively balancing the trade-off between accuracy and generalization. Additionally, functional iterative schemes enhance computational efficiency by breaking down the optimization into manageable steps. Advanced methods like gradient-based techniques and alternating minimization algorithms further accelerate convergence. These approaches also facilitate scalability, enabling TBSVMs to handle high-dimensional and large-scale datasets. Overall, iterative optimization with squared pinball loss broadens TBSVMs' applicability across complex classification tasks.